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Machine learning for additive manufacturing of implants: a review of metal and ceramic applications☆

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A R T I C L E I N F O

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A B S T R A C T

Additive manufacturing is a promising technology with impact in several industries, and it is being increasingly applied to the healthcare sector. Despite the high potential, its application in the manufacturing of implants is limited by the variability of the process and challenges related to the biological integration. In this context, machine learning has been postulated as a tool that may overcome these problems by giving support in process monitoring, optimization, and control of the implant additive manufacturing process itself.

This review systematically analyses the current state of the art regarding machine learning applications in the additive manufacturing of metallic and ceramic implants. We evaluate the integration of different machine learning algorithms and additive manufacturing technologies providing study cases where machine learning has been applied to additive manufactured bone implants. The discussion highlights the differences between the application of machine learning for additive manufacturing of metals and ceramics and how the strategies used for metal can be employed in ceramic additive manufacturing.

1. Introduction

Originally conceived for rapid prototyping, additive manufacturing (AM) has rapidly spread to several industries [1]. AM is a manufacturing technique starting with a three-dimensional Computer-Aided-Design (3D CAD) software. During the process, the material is deposited in thin and successive layers one on the top of the other, to obtain a physical and three-dimensional object [2].

In AM different materials can be used [3]. In the field addressed in this review paper, only a limited number of materials are suitable as they have to ensure biocompatibility, mechanical strength, and long-term stability in the human body. Among them, the most used materials are polymers, metals, and ceramics.

Polymers are used in implantology, mainly for specific applications such as joint components or temporary implants [4]. They are characterized by high versatility and affordability [5].

Metals, such as cobalt-chromium alloys, stainless steels, titanium [6] are used for load bearing implants because they provide mechanical strength, corrosion resistance, and good biocompatibility. Despite their higher cost, metals enable the printing of objects with high mechanical properties.

Ceramics are characterized by being difficult to manage due to their brittleness, but they can provide high temperature resistance, hardness, electrical insulating [7]. Materials such as alumina and zirconia are often used in dental and orthopaedic implants, particularly where high wear resistance and chemical stability are required.

The choice of material not only depends on the clinical application but also influences the additive manufacturing technology that can be employed, since different materials require specific processing conditions.

Among the available AM technologies [8], the international standard ISO/ASTM 52,900 classifies additive manufacturing processes into seven different categories. Some of the most common are [2]: material extrusion (MEX) [9], were the material is extruded through a nozzle and deposited layer by layer; binder jetting (BJ) [10], involving a selective deposition of a liquid binder agent on a powder material bed; Directed

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Energy Deposition (DED) [11], where focused thermal energy melts material as it is deposited; material jetting (MJ),

characterized by the deposition of build material droplets; Powder Bed Fusion (PBF) [12], which employs thermal energy to fuse regional areas of a powder bed; sheet lamination [13], used to bond layers of material into a single part; vat photopolymerization (VPP) [17], which employs light to selectively cure liquid photopolymer resins.

As listed from M. Attaran, the advantages related to these techniques are multiples [14]. First, AM allows the reduction of costs linked to molds and tooling, significantly cutting down the time-to-market, especially for prototypes. In addition, this manufacturing method enables design freedom, with a consequent possibility to have mass customization and on-demand manufacturing without excessive expenses. The efficient use of materials and the reduction of scraps contribute also to the sustainability purpose.

However, this manufacturing technique presents some limitations. W. Oropallo and L. A. Piegl noted the main challenges regarding AM [15]. Notably, there are the post processing requirements, that increase timings and costs; the printing speed, often too slow, constrain the production rates; design methodologies for AM, that is still too complex and with not adequate software; hardware and maintenance issues; and the absence of error control and feedbacks, limiting repeatability and product quality.

Today additive manufacturing is applied in various sectors [16]. For example, in the healthcare sector, it is employed for tissue engineering and dental applications [17], while in manufacturing it is used for rapid prototyping and tooling [18]. AM is widely adopted also in the aerospace, automotive and robotics sectors for components production and repair [19].

Among the many industrial fields where AM is employed, the medical sector is one of the most demanding. As highlighted in literature, the applications are several, including bioprinting of tissues and organs, anatomical models, permanent implants and scaffolds, and it results particularly suitable for prosthetic fabrication to replace missing or impairing body parts [20–22]. Indeed, AM allows to have customizable products that can be built based on the patient body structure and requirements [23]. In addition, the printed prostheses are usually cheaper and faster to produce if compared with the traditional one [22].

Additive manufacturing can be applied to both prostheses and implants. In literature, the experiments on the external ones are focused on the upper limp components, showing that AM is a very promising technology for customization and accessibility [24]. Focusing on implants, some studies showed that additive manufacturing enables the production of patient-specific implants, even with complex geometries and improved functionalities, such as a customized hip joint produced from advanced ceramic materials [25].

Despite the high impact of prosthetic manufacturing on the healthcare industry, there are some limitations and disadvantages to consider [20,22]. The AM process is characterized by a high variability that limits the predictability and reliability required for medical applications [26]. Challenges are also related to the material constraints including the need of balancing printability, mechanical properties, and biocompatibility for biological integration. In addition, post processing requirements and the lack of a clinical standardized validation are important limitations [27].

To overcome these limitations, data-driven models are recently introduced to improve process control and optimization of AM [28]. In this context, artificial intelligence (AI), and therefore machine learning (ML) and deep learning (DL), have been already applied and integrated into the manufacturing context with different goals and achieved significant operational efficiencies [29]. Talking about AM, they emerged as one of the most promising technologies to model the complex relationships between printing parameters, materials, and performance [30,31]. Artificial intelligence (AI) is a field of computer science aiming to develop a system able to perform human intelligence tasks such as reasoning, object recognition, or language processing [32,33]. Machine learning (ML) is an application of artificial intelligence that enables systems to learn from data, to identify patterns and to make decisions without being specifically programmed to do it [34,35]. A ML algorithm can perform different tasks such as classifications, regressions, clustering, feature learning, predictive analysis, etc. There exist different types of ML algorithms [35] such as supervised, when the model learns from some examples; unsupervised, where no labelled data are available; semi-supervised, working both on labelled and unlabelled data; and reinforcement learning, where the model optimizes its behaviour through rewards and penalties. The deep learning (DL) is another and more recent application of artificial intelligence including deep neural network (DNN) able to extract complex features from allowing them to perform complex activities such as image recognition, machine translation, etc [36,37]. Currently DL is the most advanced and powerful form of ML, despite it requires large datasets and significant computational resources. Other types of machine learning algorithms are already well-addressed in literature [38–40], and they are discussed in greater depth in the following section.

The use of machine learning algorithms in AM of medical parts offer the possibility to enable modelling, optimization, and control of complex interactions as well as to enhance reliability and efficiency in such a safety critical manufacturing context. In recent years, companies have demonstrated increasing interest in machine learning and deep learning algorithms for AM [41], especially on applications in the healthcare sector, and more specifically in the fabrication of implants.

However, there is a lack of clarity on the ML models available because many algorithms are still under development.

This paper aims to fill this gap by providing a bibliographic review of the main ML algorithms adopted in the healthcare sector, with an emphasis on the production of implants through additive manufacturing. The work focuses on the printing of metals and ceramic because, as demonstrated by multiple studies, they are the most common materials used for the fabrication of implants [20,22]. Through a literature analysis, this review differs from the others by focusing specifically on the synergies between additive manufacturing, machine learning, and healthcare applications. Rather than only listing ML algorithm, the review summarizes the existing literature according to the level of ML integration and maturity of the process modelling. The review analyses how ML is coupled with AM workflows and how the level of integration differs between metal and ceramic implant manufacturing.

2. Machine learning algorithms

As anticipated in the introduction, during the past, many machine learning algorithms were developed and applied across different research fields. Some of the most used are supervised learning, unsupervised learning, reinforcement learning, regression algorithms, neural network, deep learning, support vector machine, k-means clustering, decision tree, and random forest. Each of these algorithms is described below.

- *Supervised learning*

Supervised learning is a type of machine learning in which models learn from labelled data. It is divided into two phases: training, where the model learns the relationship between input and labels, and testing, where the model is evaluated on its ability to perform the task independently on new data [42]. Usually, labels correspond to different classes in classification problems [43], and they allow the model to learn from past data, where the target output is already known during the training.

- *Unsupervised learning*

On the other hand, unsupervised learning does not involve labelled data: it aims to learning patterns, structures, or hidden relationships, rather than focusing on classification tasks [44]. In this case, a larger amount of data is required to properly train the model, and the model learns the relationships between inputs and outputs autonomously [45]. There exists also the *semi-supervised learning* that employs both labelled and unlabelled data [46]: it involves a small amount of labelled data, which are expensive to obtain, and a large amount of unlabelled data. In this way, the cost of annotations is reduced while still increasing the model's performance.

- *Reinforcement learning*

Reinforcement learning is a machine learning framework based on agents that optimize their behaviour by interacting with the environment. The system does not require labels, but it learns to make decisions by penalties or rewards based on its actions. The final aim of the reinforcement learning is to maximize the cumulative rewards over time [47].

- *Regression algorithms*

Regression algorithms are computational methods to predict a new value based on past data with a certain level of accuracy [48]. Based on the type of relationships among data, there exist different types of regression algorithms such as *linear regression*, *multivariate regression,* or *polynomial regression* [49]. Even if they are basic models, they are characterised by high level of versatility. The regression algorithms are already applied in different fields, such as the economic, marketing, medicine, and engineering [50].

- *Neural network*

Neural networks are computational models inspired by the human brain [51], composed of interconnected neurons and organized in layers. Neural networks typically consist of three types of layers: an input layer, which receives the raw data; hidden layers, which extracts data features; and an output layer, which produces the predictions [52]. Data flow through the network: a network is considered deeper as the number of hidden layers increases [53]. The training is based on the *backpropagation algorithm* [54,55], that adjusts the weights to minimize the error between predictions and targets. Neural networks are widely used due to their versatility, as they can learn complex relationships directly from data. In addition, hybrid approaches combining neural networks with fuzzy logic, such as the Adaptive Neuro-Fuzzy Inference System (ANFIS), have been developed to integrate the learning capability with the interpretability of fuzzy systems [56].

- *Deep learning*

Deep learning, as anticipated, is a subset of machine learning [37]. It focuses on deep neural networks, i.e. neural networks with many hidden layers, to extract complex relationships within the data. These networks are capable of learning nonlinear and high-level features directly from data, making them suitable for high dimensional tasks such as text, image, or video analysis [57]. There are different types of deep neural networks such as Convolutional neural networks (CNNs), Recurrent neural networks (RNNs), Transformers, etc.

- *Support Vector Machine*

Support Vector Machines (SVMs) are computational models that learn to assign labels based on training examples [58]. Their functioning is based on the identification of the best decision boundary that divides classes, called hyperplane [59]. The name comes from support vectors: data points closest to the hyperplane. They are mainly employed to perform regression, classification, and analysis of outliers [60]. SVMs are useful in applications characterized by complexity and high dimensionality, such as the healthcare sector [61].

- *K-means clustering*

K-means clustering is an unsupervised algorithm to group unlabelled data into subsets with similar characteristics, called clusters [62]. Every cluster is associated with a centroid, which represents the mean of the data points of that cluster. The algorithm associates each data point with the closest centroid, assigning it to that cluster [63,64]. The number of clusters is decided by the user: the most common method is the elbow method [65]. The K-means clustering is computationally easy and scalable to large amounts of data.

- *Decision tree*

Decision trees are supervised algorithms usually employed for both regression and classification [66]. Starting from the first node, called root, it recursively splits data into homogeneous subsets. At each step, the algorithm selects the features and threshold to obtain the best possible data split based on defined criteria [67]. Its main advantage is the high interpretability. Recent studies focus on further development of the decision tree algorithms, particularly in terms of approximation accuracy, interpretability, and generalization [68].

- *Random forest*

Random forests are supervised learning algorithms based on a set of decision trees, each trained on slightly different subset of the data [69]. The outcome is the combination of output of individual trees, and they can be combined through majority voting in classification tasks and averaging in regression tasks [70]. Random forests rely on two main mechanisms: bootstrap aggregating and random feature selection at each split [71]. Owing to these mechanisms, random forest is versatile and often achieve high predictive accuracy.

3. Review methodology

This review aims to provide a comprehensive overview of the application of machine learning to the additive manufacturing of implants, focusing on metals and ceramics. The scientific papers analysed in this work were retrieved from online databases such as Google Scholar and Scopus. The keywords employed included machine learning, artificial intelligence, 3D printing, additive manufacturing, implants, prostheses, metal, ceramic, and others. In Table 1 it is reported an example of the query employed to search for articles involving machine learning for AM of metal implants. The selected articles were published between 2020 and 2026, highlighting the newness and novelty of these topics. All acronyms used throughout the manuscript are reported in the final glossary.

To move beyond a descriptive comparison of individual studies, the

Table 1
Query example.

Machine learning for AM of metal implants	((“machine learning” OR “artificial intelligence” OR “deep learning” OR “neural network*” OR “support vector machine*” OR “random forest*” OR “gaussian process*”) AND (“additive manufacturing” OR “3D printing” OR “selective laser melting” OR “laser powder bed fusion” OR “electron beam melting” OR “directed energy deposition”) AND (prosthes* OR implant* OR “orthopedic implant*” OR “biomedical implant*” OR “bone implant*” OR “hip prosthesis” OR “knee implant”) AND (metal* OR titanium OR “titanium alloy*” OR “Ti-6Al-4 V” OR cobalt OR “Co-Cr” OR steel))

selected papers were analysed based on the workflow stage, the ML function, the validation and maturity levels. Only articles written in English specifically addressing machine learning algorithms applied to AM of implants and prostheses made of metal or ceramics were included. Papers about other industries or other topics were excluded. Preference was given to papers reporting actual experiments and case studies involving machine learning in implants manufacturing. Although this review aims to be comprehensive, limitations may arise from publication bias and the exclusion of papers written in other languages. The criteria adopted for this review are reported in Table 2.

4. Classification

Among the numerous papers analysed, 28 articles were included in this review and were classified based on the additive manufactured materials, metals, or ceramics. The screening process was performed sequentially. The literature search initially identified approximately 300 records from the Scopus and Google Scholar databases. After removing duplicates and applying sequential screening criteria based on language (English), technology (additive manufacturing), application (machine learning in implant manufacturing), material type (metals or ceramics), 28 studies were finally selected and included in the review. The study selection process is reported in Fig. 1.

Table 3 and Table 4 provide an overview of the studies using metals and ceramics, respectively. These tables include the AM technology employed, the material used, the machine learning models tested, and the main applications of ML.

5. State of the art

The following sections describe the application of machine learning to AM of implants divided according to the material type, namely metals and ceramics.

5.1. ML in metals printing

As demonstrated in multiple studies, metals are among the most suitable materials for the AM of prostheses. In some cases, metal additive manufactured objects can be produced using composite materials. They typically include polymers, like PolyLactic Acid (PLA), and metal

Table 2
Inclusion and exclusion criteria.

Inclusion criteria	Exclusion criteria
– Paper written in English	– Paper written in other languages than English – Absence of machine learning methods – Absence of AM – Absence of AM technologies to produce implants – Machine learning not applied to AM process – Studies limited to polymeric, resin-based, or purely materials other than metal and ceramic
– Application of machine learning techniques	– General reviews without methodological contribution to ML-based manufacturing
– AM applied to the fabrication of medical devices	– Studies that report additive manufacturing processes without integrating data-driven or learning-based approaches
– Direct integration of machine learning with the AM	
– Use of metal or ceramic materials with additive manufacturing technologies	
– Focus on biomedical implants or internal prosthetic applications	
– Quantitative evaluation of process, material, or model performance	
– Experimental validation using real manufacturing or process data	

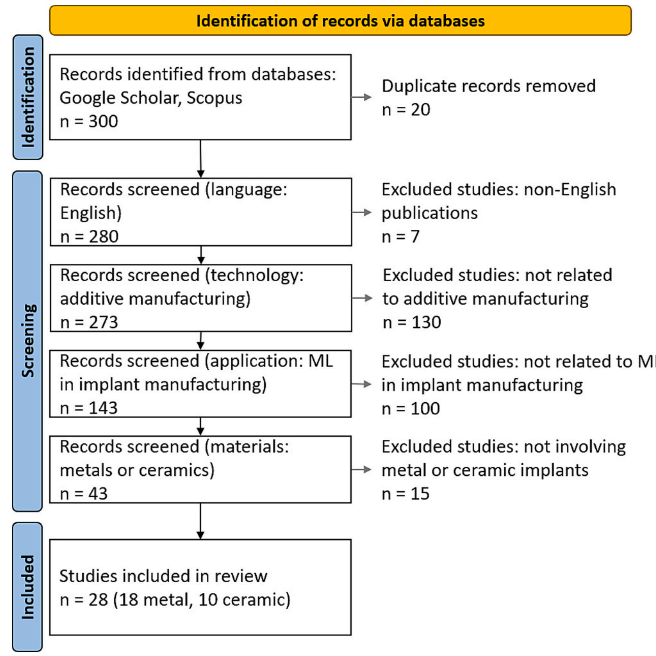

Fig. 1. Flow diagram illustrating the study selection process for the literature review.

components, creating a metal-filled filament [72]. When high metallic content filaments are employed, the use of metals enables high mechanical properties, rigidity, corrosion resistance, and biocompatibility [72]. However, metal AM may result in surface roughness and process-induced defects, requiring surface post-treatments for biomedical implants [73].

As demonstrated by R. Asadi *et al.* and A. Caggiano *et al.*, machine learning techniques have been applied to various metal additive manufacturing processes, such as the Direct Energy Deposition and Selective Laser Melting manufacturing processes, for monitoring and quality control [74,75]. Regarding the AM of implants, there are some studies in the literature that demonstrate the effectiveness of machine learning applied to additive manufacturing for implants [76,77].

5.1.1. General structures for metal additive manufacturing

Cellular, lattices or porous structures are fundamental for the effective use of metal materials in the AM of implants. Several studies have explored the use of ML to model and predict the behaviour of these complex architectures, highlighting the potential of data-driven approaches to replace traditional trial-and-error methods.

A first group of studies focuses on the prediction of mechanical behaviour from geometrical and structural information. H. Hassanin *et al.* [78] compared the performance of different network architectures to predict the mechanical properties of titanium alloy cellular structures fabricated via Laser Powder Bed Fusion (LPBF). More in detail, the study was conducted comparing shallow neural networks (SNNs), deep neural networks (DNNs), deep learning neural networks (DLNNs), together with the traditional design of experiments (DoE) approach. By using the strut length, diameter, and orientation angle, the models predicted the ultimate strength, Young's modulus, and specific strength. Their results showed that deep learning-based approaches outperform the others, demonstrating the capability of deep learning to capture nonlinear relationships between geometric parameters and mechanical responses. Similarly, S. Gao *et al.* [79] compared different machine learning techniques to predict the impact of structural and mechanical factors on the fatigue life of porous titanium structures, used for implants fabrication. The analysis was conducted on AM geometric parts manufactured by the Electron Beam Powder Bed Fusion (EB-PBF) process. The machine learning methods tested were multiple linear regression, artificial neural

Table 3
Summary of machine learning applications in metal additive manufactured implants. The material column reports the main metallic material or alloy investigated. All acronyms used are reported in the final glossary.

Reference	AM technology	Material	Machine Learning	Application
H. Hassanin *et al.* [78]	Laser Powder Bed Fusion	Titanium	SNN, DNN, DLNN	Mechanical properties of metal lattice structures
S. Gao *et al.* [79]	Electron Beam Powder Bed Fusion	Titanium	Multiple linear regression, ANN, support vector machines, and random forests	Impact of structural and mechanical factors on fatigue life
N. Gerdes et al. [80]	Laser Powder Bed Fusion	Magnesium	CNN	Surface roughness
T. Bhardwaj and M. Shukla [81]	Direct Energy Deposition	Titanium	ANN	Track dilution generated in single-track deposition
R. Alkentar and T. Mankovits [82]	Simulation only	Titanium	Linear regression algorithm	Porosity of the lattice structure for hip implants
W. Ying et al. [83]	Material Jetting	Titanium + PDMS + Hydroxyapatite	3D-Printing NN Co-modelling	Bone quality and stress distribution after implantation of hip implant
D. Milone et al. [84]	Design only	Stainless steel	CNN	Hip prostheses design
B. Peng et al. [85]	Laser Powder Bed Fusion	Titanium and zinc	GAD-MALL	Mechanical characteristics of orthopaedic implants
A. F. Bonatti et al. [86]	Electron Beam Melting	Cobalt-Chromium	Rule-based expert system	Porosity layer by layer for tibial trays
M. A. Kurtz et al. [87]	Laser Melting – Powder Bed Fusion	Titanium	K-means clustering	Long-term reliability and behaviour of metallic implants
M. U. Zaheer et al. [88]	Selective Laser Melting	Titanium	Several ML models, including random forest, ANN, polynomial regression	Healing progression after tibial bone implantation
T. A. Burge et al. [89]	Laser Powder Bed Fusion	Titanium	CNN	Automatic extraction of anatomical data from CT images for tibial implant design
S. Zhao et al. [90]	Selective Laser Melting / Laser Powder Bed Fusion	Zinc–copper alloy	Gaussian Process Regression (GPR)	Part density for bone implants
R. Alkentar et al. [91]	Selective Laser Melting	Titanium	NN, GPR, Decision Tree	Mechanical behaviour of the femoral stems
C. Wu et al. [92]	Laser Powder Bed Fusion	Titanium	Derivative-aware NN	Reconstruction of mandibular bone (or femoral bone)
N. Beisekenov et al. [93]	Direct Metal Laser Sintering	Titanium	ANN, Bayesian network	Predict stress, displacement, and stiffness of mandibular bone
C. Çalışkan et al. [94]	Laser Powder Bed Fusion	Cobalt-Chromium	ANN	Mechanical properties of dental prostheses
Y. Chen et al. [95]	Simulation only	Titanium	CNN	Topology optimization of full-arch dental implants

Table 4
Summary of machine learning applications in ceramic additive manufactured implants. The material column reports the main ceramic material investigated. All acronyms used are reported in the final glossary.

Reference	AM technology	Material	Machine Learning	Application
J. Zhou et al. [96]	Direct Ink Writing	Zirconia	Several ML models including Extreme gradient boosting, Regression Algorithm, random boosting,	Material deposition quality
Y. Liu et al. [97]	Digital Light Processing	Calcium phosphate	XGBoost	Optimal structure for osteoinductivity
S. Ibrahimi et al. [98]	Vat Photopolymerization	Calcium hydroxyapatite	Linear and nonlinear algorithms	Parameter definition, topology classification
M. Fielder and A. K. Nair [99]	Material Extrusion	Calcium hydroxyapatite	K-means clustering, Support Vector Machine and Gaussian Mixture Model	Bone growth after ultrasound stimulation
F.T. Omigbodun and B. I. Oladapo [100]	Fused Deposition Modelling	PLA + Calcium Hydroxyapatite	ML algorithm – not specified	Optimize lattice structure, improve porosity, and other characteristics
F. T. Omigbodun et al. [101]	Fused Deposition Modelling	PLA + Calcium Hydroxyapatite	XGBoost, AdaBoost, Random Forest, K-Nearest Neighbour, and Linear Regression	Compressive and tensile strength of porous scaffolds
M. M. Bappy et al. [102]	Material Extrusion	PLGA + nano-Hydroxyapatite	Nonlinear polynomial regression model	Optimize the strut width
C. Wu et al. [103]	Lithography-based Ceramic Manufacturing	Structural bioactive ceramic	U-Net NN	Bone regeneration outcomes of a sheep tibia
C. Wu et al. [104]	Direct Ink Writing	Sr-HT-Gahnite	Fully Connected NN	Bone-ingrowth prediction in a sheep tibia model
J. Zhang et al. [105]	Digital Light Processing	Biphasic Calcium Phosphate	Fully Connected NN	Optimal design of cranial implants

networks (ANNs), support vector machines, and random forests. Among the tested models, support vector machines achieved the best predictive performance, confirming their robustness in handling complex and multi-factor relationships. The workflow employed is reported in Fig. 2.

A second group of studies moves from structural-property prediction toward process monitoring. N. Gerdes *et al.* [80] proposed a deep learning-based in-situ monitoring approach for LPBF of a magnesium alloy suitable for implant application. A convolutional neural network (CNN) was used to analyse the hyperspectral images acquired during the fabrication process to predict the surface roughness, showing high accuracy and highlighting the potential of ML for real-time quality control.

A third direction concerns process-parameter optimization. Process parameter optimisation is another key application area. T. Bhardwaj and M. Shukla [81] conducted a study on titanium alloys for biomedical implants, proposing a machine learning approach for the Direct Energy Deposition (DED) additive manufacturing process. They developed an ANN that used the printing parameters such as laser power, scan speed, and powder feed rate to predict the track dilution generated in single-track deposition of material. This parameter is particularly relevant in the context of implants because it is directly linked to the metallurgical quality of the part, making ML a valuable tool for improving structural integrity in implant manufacturing.

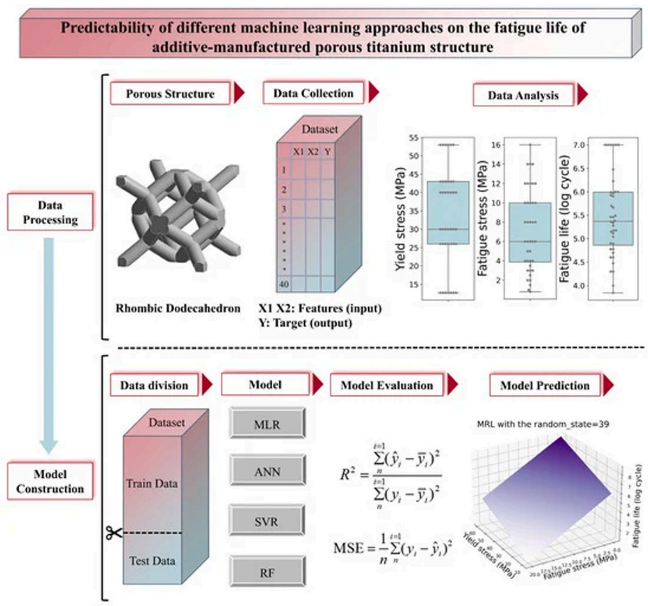

Fig. 2. Machine learning process flowchart of predicting fatigue life with the synergic effect of yield stress and fatigue stress,
reproduced from [79].

Overall, these studies show a progressive evolution of ML in metal implant additive manufacturing from the prediction of lattice mechanical properties to the optimization of process parameters. This progression confirms that metal systems provide direct and measurable data, which explains the higher maturity of ML applications in this field.

5.1.2. *Load bearing metal implants*

In the reviewed studies, ML applications for load-bearing metal implants can be grouped into four main functions: lattice and porosity design, patient-specific biomechanical modelling, multi-objective optimization of implant architectures, and quality or reliability assessment. This shows that ML is progressively evolving from simple geometric prediction toward integrated workflows.

One of the main applications of metal AM for implants is related to hip replacements. In this context, machine learning is widely used to support both design optimization and patient-specific customization.

In this context, R. Alkentar and T. Mankovits [82] proposed a machine learning application to estimate the best parameters for AM metallic hip implants featuring CAD lattice structures. A supervised machine learning model based on linear regression and implemented with scikit-learn was applied to predict lattice porosity from unit-cell geometry parameters. The results showed high predictive accuracy, demonstrating that even simple machine learning models can be useful in the design of additive manufactured metallic hips prostheses. Fig. 3 reports the hip implant design with different lattice structures. Fig. 4 reports the model's performance about porosity predictions in three cases corresponding to three different configurations.

A second research direction concerns patient-specific biomechanical modelling, in which ML is combined with experimental, imaging, or motion-related data. W. Ying *et al.* [83] employed neural networks for creating personalized hip implants made of polymers, metals, and ceramic powders. In the study, experimental data obtained from additive manufactured biomimetic bone models were combined with machine learning models based on multilayer perceptron neural networks. They proposed a 3D Printing Neural Network Co-modelling (3DPNN) framework that employed five selected geometry descriptors to predict biomechanical patient-specific characteristics and image optimization. By combining experimental data and neural networks, the framework enables both forward prediction of stress distribution and inverse prediction of bone quality, representing a significant step toward digital twins in implant design.

With the same perspective, D. Milone *et al.* [84] created a stainless steel (AISI 316 L) customized hip implant by integrating additive manufacturing and machine learning-based design approach. In their study, deep learning was applied to motion capture data with the aim of extracting subject-specific gait kinematics, which were subsequently used within multibody and finite element models to evaluate implant loading conditions.

Beyond hip implants, machine learning can be applied to the metal AM of different orthopaedic components. The literature includes several studies investigating the use of machine learning in the additive manufacturing of lower limb implants. This design-oriented use of ML is demonstrated by B. Peng *et al.* [85], who proposed a machine learning application for the high-dimensional multi-property optimization of

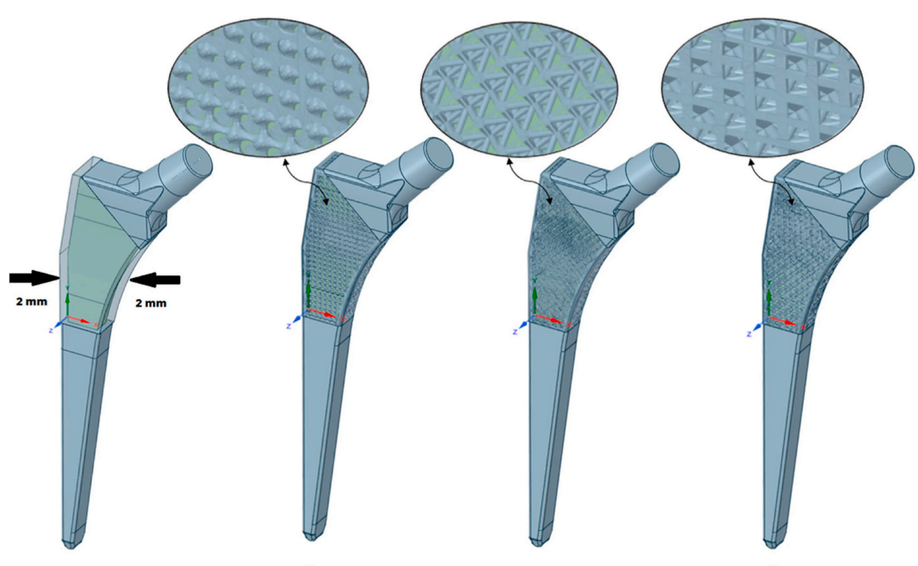

Fig. 3. (a) Hip implant design with different type of lattice structures. More in detail (b) 3D-lattice infill, (c) double-pyramid lattice and face diagonals, (d) octahedral lattice,
reproduced from [82].

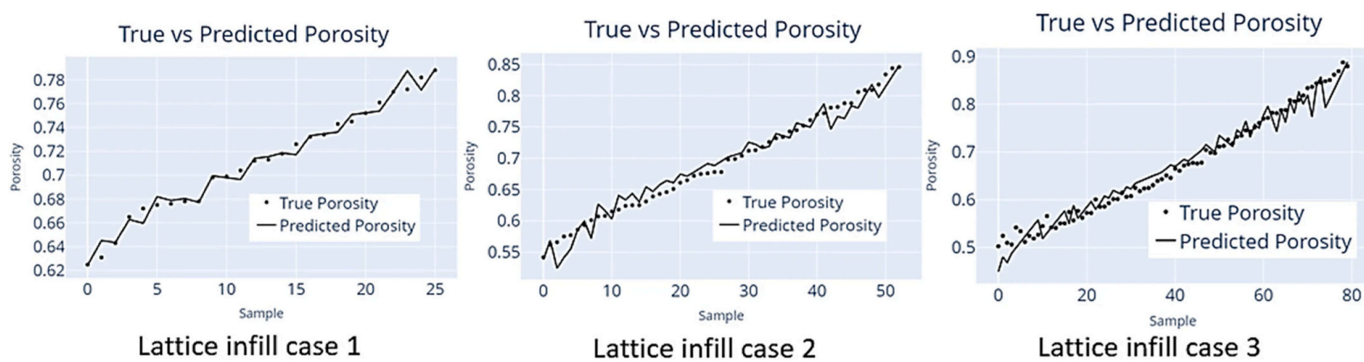

Fig. 4. Performance in porosity predictions in three cases, adapted from [82].

additive manufactured architected materials. They developed the "GAD-MALL" method, which combines generative architecture design with a multi-objective active learning loop to explore the design space. The parts were fabricated in titanium and zinc by the LPBF technology. Machine learning was applied during the design of architected metallic scaffolds for orthopaedic implants to optimise elastic modulus, yield strength, and manufacturability constraints. This approach allows efficient exploration of high-dimensional design spaces, optimizing mechanical properties and manufacturability simultaneously. Fig. 5 shows the workflow applied.

A fourth group of studies include ML in quality assurance and reliability assessment. A. F. Bonatti *et al.* [86] focused on cobalt-chrome alloy tibial trays printed by Electron Beam Melting (EBM), a technique that uses a high-energy electron beam to selectively melt powder layers of materials. They applied an expert system for online defect detection, focusing on porosity detection through layer-by-layer image evaluation. Although simply based on rule-driven image analysis rather than deep learning, this study represents a relevant example of rule-based AI applied to the manufacturing of implants in the healthcare sector.

Complementing online defect detection, M. A. Kurtz *et al.* [87] showed that machine learning techniques can also be applied to evaluate the post-processing reliability and performance of metal additively manufactured implants produced by SLM-PBF, such as titanium tibial baseplates and acetabular cups. Using K-means clustering, an unsupervised machine learning method, they evaluate the long-term reliability focusing on the corrosion phenomena in additively manufactured metal implants. This study demonstrates the effectiveness of unsupervised learning for post-processing analysis and reliability assessment.

More recent studies indicate a further shift toward predictive and decision-support frameworks. M. U. Zaheer *et al.* [88] employed Selective Laser Melting (SLM) technology to produce titanium alloy tibial knee implants. An AI-assisted framework was used for the design and evaluation of the fabricated prostheses. More in detail, different supervised machine learning algorithms– including Random Forest, XGBoost, Gradient Boosting and artificial neural networks (ANNs)– were applied to predict biomechanical and biological characteristics, such as the bone callus stiffness and post-implantation healing trends of the patient.

T. A. Burge *et al.* [89] proposed a machine learning-based pipeline for customizable titanium tibial implants with lattice structures. The implants were produced via LPBF and designed to guarantee modular stiffness tailored to patient-specific bone characteristics. The aim was to minimize the stress shielding and optimize the bone remodelling after implantation. In this study, convolutional neural networks (CNNs) were employed for the automatic extraction of anatomical and biological data from the patient images.

S. Zhao *et al.* [90] applied a supervised machine learning to optimize SLM and LPBF printing parameters of a zinc-copper alloy used in bone implants. More in details, they employed the Gaussian Process Regression (GPR) model that, starting from laser power and scanning speed, predicted the part density. The algorithm demonstrated high predictive accuracy, but also sensitivity to dataset size, underlining the importance of data quality.

Finally, another study using SLM technique was conducted by R. Alkentar *et al.* [91], who fabricated a titanium femoral stem with lattice structures. Using the Finite Element Method (FEM), they created a dataset linking geometrical parameters and patient-specific physical characteristics to mechanical responses such as deformations, stress and strain energy. A supervised machine learning algorithm was employed to predict these mechanical properties, creating a predictive dataset for surgical decision support. This work represents an example of machine learning applied to the design of additively manufactured metallic hip implants, using a predictive framework that can support surgical

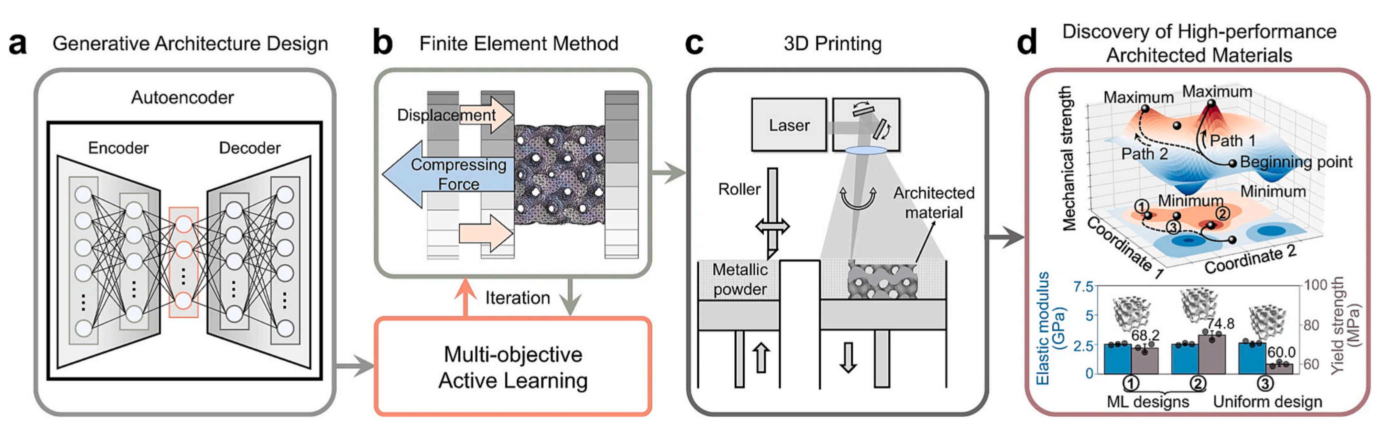

Fig. 5. An overview of the proposed workflow, reproduced from [85].

decision-making.

The reviewed studies show that ML in load-bearing metal implants is evolving along a clear maturity pathway, supporting that metal implant AM provides sufficiently measurable and structured data to validate integrated ML workflows.

5.1.3. Craniofacial metal implants

Another application of metal AM concerns craniofacial implants, where ML techniques are increasingly being adopted. In this field, ML is mainly used for topology optimization and patient-specific reconstruction. C. Wu *et al.* [92] applied machine learning as a surrogate modelling to optimize the topology of functionally graded reticular structure, such as mandibular (Fig. 6) or femoral bones. They applied a Derivative-Aware Neural Network (DANN) on titanium parts produced by LPBF process to predict both mechanical response and gradient information as functions of design parameters. The proposed approach enabled efficient design, but the computational cost and the process constraints remained significant challenges.

Within this design-oriented perspective, N. Beisekenov *et al.* [93] integrated a data-driven framework into the design of additive manufactured titanium prostheses for mandibular reconstruction, allowing real-time evaluation during the design phase. Artificial neural networks were employed as surrogate models to predict biomechanical characteristics in real time, such as stress and displacement.

Extending this approach to dental prostheses, C. Çalışkan *et al.* [94] investigated the mechanical behaviour of LPBF-fabricated cobalt alloy dental prosthetic incorporating gyroid lattice structures. An artificial neural network was used as a surrogate model to predict flexural strength. The network achieved high predictive accuracy, confirming the suitability of ML for modelling mechanical properties of complex lattice geometries.

In the context of property prediction, Y. Chen *et al.* [95] also applied machine learning to the dental field. More in details, they fabricated a titanium full-arch implants and developed a convolutional neural network-based framework, named BESO-net, to identify the optimal structural topology, enabling material reduction while maintaining structural strength. Fig. 7 reports the complete workflow adopted in this case study [95].

Overall, these studies indicate that, in craniofacial applications, ML primarily acts as a bridge between anatomical customization, structural optimization, and implant geometries. Compared with load-bearing orthopaedic implants, the focus is less on process monitoring and more on accelerating patient-specific design while maintaining mechanical reliability.

5.2. ML in ceramics printing

With regards to ceramic implants, they can be fabricated using different additive manufacturing techniques [106]. The main advantage of ceramics lies in their ability to enable the production of customized geometries for biomedical applications. However, the AM of ceramic is characterized by strong interdependence between material, printing parameters, and post-processing activities, which highlights the potential contribution of machine learning techniques [107,108]. The integration of machine learning techniques with ceramics additive manufacturing enables the prediction of relationships among structural design, mechanical properties, and biological responses of implants, overcoming the limitations of traditional trial-and-error approaches [109].

Different types of ceramic can be used, for example Al_2O_3, ZrO_2, hydroxyapatite, etc. [110], and the filament usually includes some polymeric binders [111]. As demonstrated by F. Tarak *et al.* [112], machine learning, such as artificial neural networks, can be applied also help in deciding the optimal binder combination.

5.2.1. General structures for ceramic additive manufacturing

Starting from the study of the materials and structures, filament geometry during extrusion for AM implants plays a fundamental role, as it affects the porosity, dimensional accuracy, and reliability of the printed parts. In the reviewed ceramic studies, ML is mainly used to support design exploration, structure and property prediction, and dimensional optimization, rather than real-time process monitoring. This indicates that ML applications in ceramic implant manufacturing are still concentrated at the design and pre-validation stages, reflecting the complexity of ceramic processing and the strong influence of post-processing steps.

In this context, J. Zhou *et al.* [96] investigated the quality of deposition lines using zirconia ceramic paste in Direct Ink Writing (DIW) additive manufacturing process. By applying machine learning algorithms, specifically XGBoost-based regressor and classifiers, they analysed the relationships between extrusion parameters and deposition quality, establishing quantitative relationships between them.

Similarly, Y. Liu *et al.* [97], proposed an application of machine learning to the fabrication of calcium phosphate ceramic scaffolds via Digital Light Processing (DLP). They employed XGBoost (Gradient Boosting Decision Trees) to correlate specific surface areas and permeability with osteogenic outcomes, demonstrating how ML can directly support the design of osteoinductive scaffolds.

Beyond these correlations, ML has also been used to address inverse design problems to define scaffold parameters. S. Ibrahimi *et al.* [98] discussed the use of machine learning to solve the inverse problem of determining the parameters of Triply Periodic Minimal Surfaces (TPMS) in ceramic scaffolds. The models were applied to hydroxyapatite parts with target values coming from additive manufactured trabecular-like ceramic scaffold fabricated via Vat Photopolymerization followed by sintering. The authors tested a linear and two nonlinear machine learning models to predict TPSM parameters and classify the scaffold topology.

In addition to structural design, ML has been applied to predict biological responses. M. Fielder and A. K. Nair [99] proposed a machine learning-based framework to predict and classify bone growth after ultrasound stimulations in additive manufactured ceramic scaffolds. They

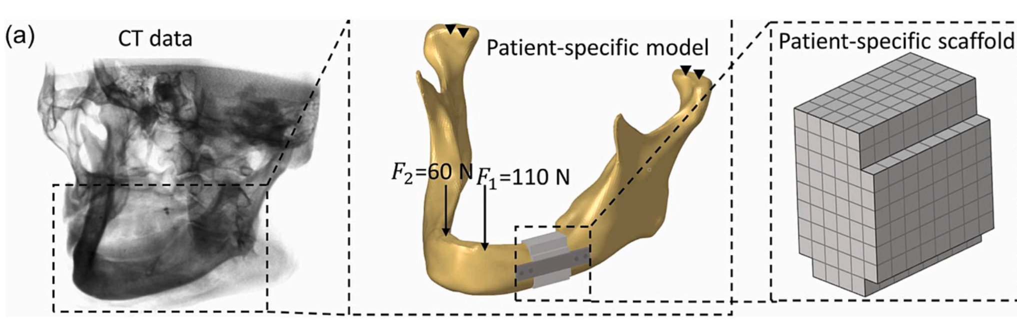

Fig. 6. A patient-specific design of the bone scaffold for mandibular reconstruction, adapted from [92].

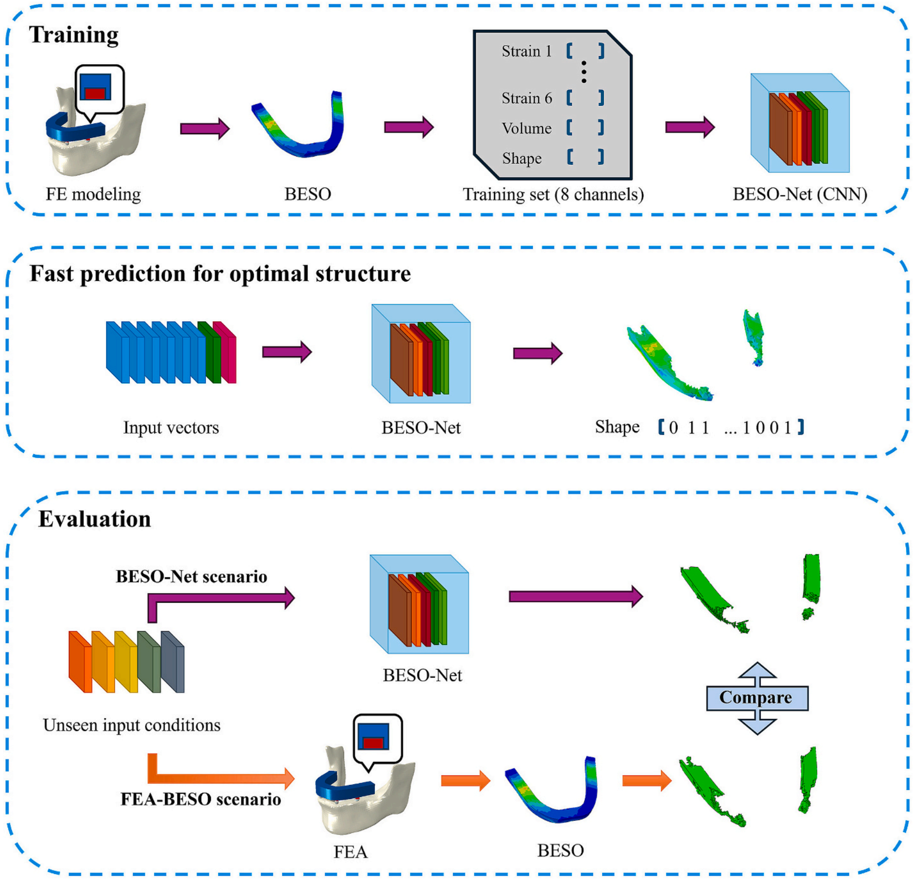

Fig. 7. Workflow of the proposed approach, reproduced from [95].

compared different ML algorithms, showing that supervised methods, particularly SVM, outperform unsupervised approaches in capturing complex biological behaviours.

Another recurring feature of ceramic scaffold studies is the use of a PLA binder, where it allows to handle and extrude the materials while adding variability of the process. Within this context, F.T. Omigbodun and B. I. Oladapo [100] employed a human-AI-driven design framework for lattice-structured bone scaffolds with a significant PLA content in the filament. Machine learning models were used to predict porosity, strut thickness, and energy absorption of additive manufactured parts with Fused Deposition Modelling (FDM).

A further development of this approach is reported in F. T. Omigbodun *et al.* [101], where they used FDM to print bone scaffolds in PLA reinforced with calcium hydroxyapatite. Fig. 8 reports the work setup where they applied ML algorithms, in particular XGBoost, AdaBoost, Random Forest, K-Nearest Neighbour, and Linear Regression, to predict the compressive and tensile strength based on filament composition and mechanical properties, highlighting the effectiveness of ensemble methods in modelling complex material behaviours. The resulting performance on the compression are shown in Fig. 9.

Finally, some studies move closer to process-parameter optimization, although still mainly at the level of dimensional control rather than full process monitoring. M. M. Bappy *et al.* [102] used a nonlinear polynomial regression model to optimize the strut width of bone scaffolds fabricated via material extrusion using polymer-ceramic composite materials. They demonstrated that even relatively simple models can effectively improve dimensional accuracy in extrusion-based processes.

These studies show reflect the more indirect relationship between printing parameters and final ceramic performance, which is strongly influenced by filament composition and post processing activities.

5.2.2. *Load bearing ceramic implants*

As for metals, load bearing implants are one of the most relevant application areas for ceramics AM. However, compared to metals, the application of machine learning in this field is still mainly limited to design and simulation stages. In this context, C. Wu *et al.* [103] conducted a study on bone regeneration using a machine learning-based design, with a representative example of a sheep tibia. Ceramic additive manufactured scaffolds composed of Triply Periodic Minimal Surfaces (TPMS) was fabricated via Lithography-based Ceramic Manufacturing (LCM) process. A U-Net was used to predict the local micro-strains starting from a voxel map of Young's modulus, while Bayesian Optimization was applied to optimize the results maximising the bone density over time. Fig. 10 and Fig. 11 report the study workflow and the modelling.

In another study, C. Wu *et al.* [104] used robocasting to produce ceramic cylindrical shape porous scaffolds. Fully connected neural networks were implemented to accelerate the simulation phase by predicting the ingrown outcomes of a tibia bone implanted in a sheep.

As mentioned above, W. Ying *et al.* [83] proposed a neural network for creating personalized hip implants from composite materials consisting of polymeric, metallic, and ceramic powders. They authors used a 3D Printing Neural Network Co-modelling (3DPNN) framework to predict the bone quality and the stress distribution after implantation.

Overall, these studies show the limited process integration reflecting the greater complexity of ceramic manufacturing.

5.2.3. *Craniofacial ceramic implants*

Another application of ceramic additive manufactured implants concerns facial and craniofacial bone reconstructions. In this field, the literature is still limited, and to date, only one case study has been

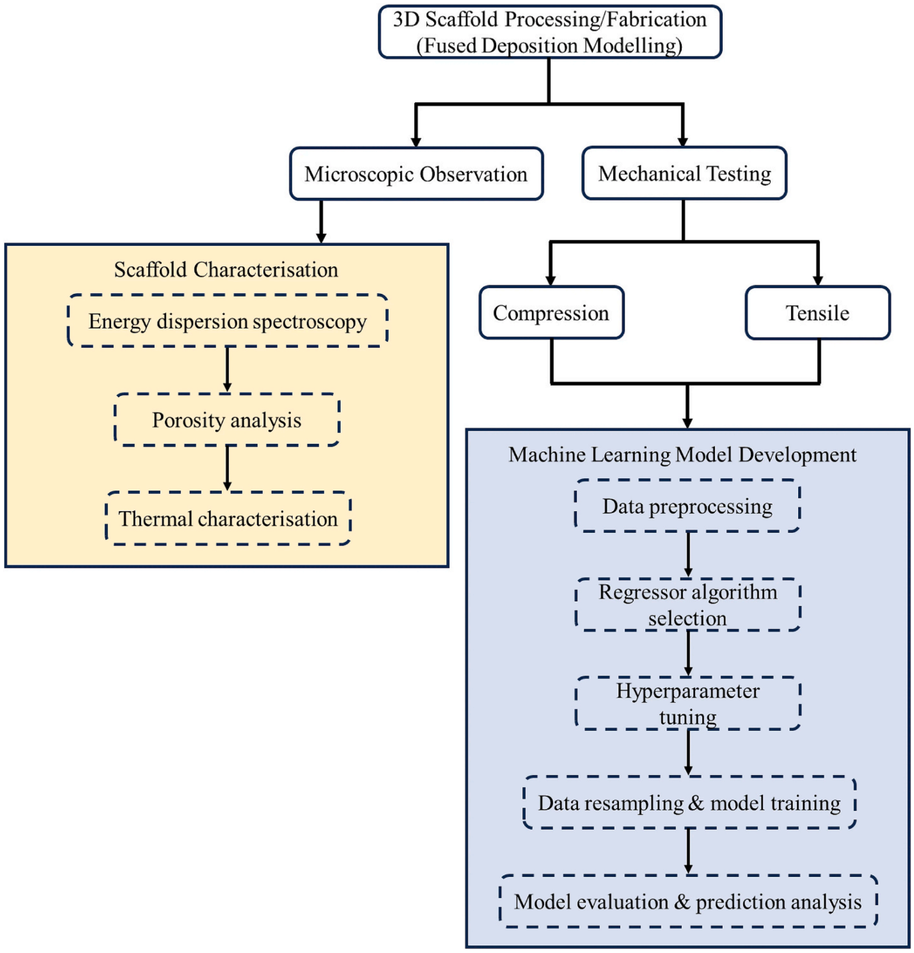

Fig. 8. Research workflow, reproduced from [101].

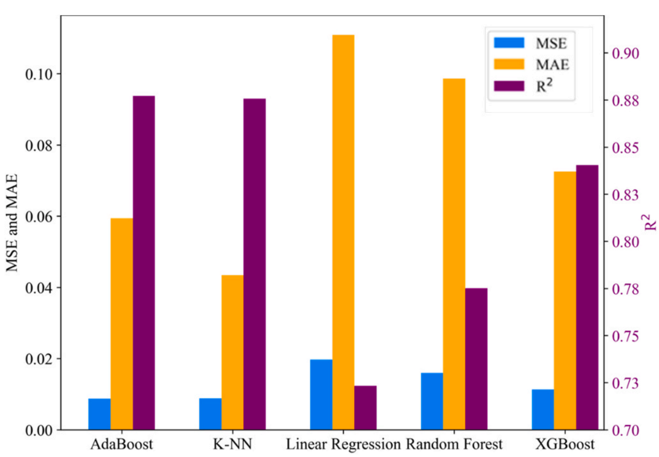

Fig. 9. Model performance result for compression material property prediction, reproduced from [101].

reported.

J. Zhang *et al.* [105] proposed a complete inverse design machine learning-driven pipeline of craniofacial osteoinductive implants. Porous ceramic scaffolds made of Biphasic Calcium Phosphate (BCP) were fabricated using a DLP-based ceramic additive manufacturing process, they printed. A Fully Connected Neural Network (FCNN) was employed to define the best design for printing the skull part, balancing rigidity and osteoinduction while avoiding stress shielding and brittleness.

Even though ceramic craniofacial applications remain at an early stage, this study shows that ML can support anatomically specific implant design by employing a single optimization framework.

6. Comparison and discussion

From the analyses conducted in this paper, it is evident that significant differences exist in the literature between the application of machine learning to the AM of implants in metal and in ceramic. However, contrasts emerge in terms of the specific machine learning strategies adopted and their level of integration within the manufacturing workflow. This gap is also mechanical: metal ML is more mature because the process parameters, properties and defects are more observable and data rich; ceramic ML that is still depending on multi-stage transformations and post process activities that make variable relationships more indirect, nonlinear, and difficult to monitor.

6.1. ML–AM coupling mechanisms and process-related problems addressed by ML

The coupling between machine learning and additive manufacturing is based on the ability of ML models to link process inputs, process signatures, structural features, and final implant performance. In AM, the quality and performance of the printed parts depend by the interaction between material properties, geometry, process parameters, and post-processing condition. The relationships between these variables are often nonlinear, hidden, and difficult to describe. ML is therefore

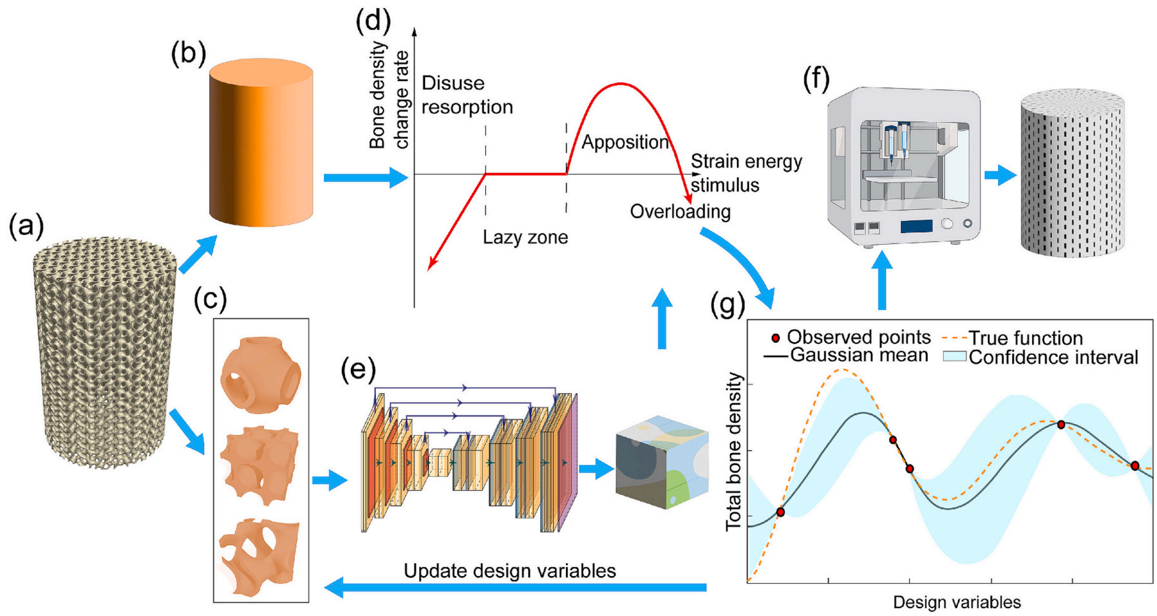

Fig. 10. Schematic of the ML-driven design framework. Machine learning is employed at the microscale through a U-Net neural network (e) to predict micro-strain components, and through Bayesian optimisation (g) to iteratively optimise micro unit cell geometry based on predicted bone growth performance, reproduced from [103].

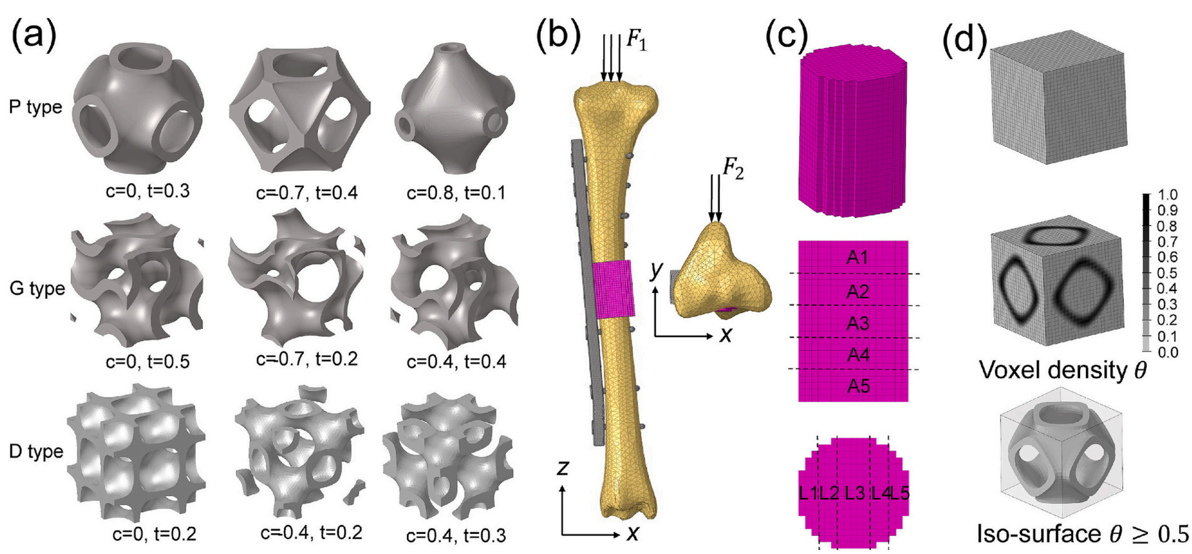

Fig. 11. Multi-scale in-silico modelling of TPMS-based scaffolds for a segmental sheep tibia defect, including parametrised unit cells (P, G, D types), the macroscopic FE model with graded regions (A1–A5, L1–L5), and the voxel-based microscopic unit cell used for bone reconstruction, reproduced from [103].

helping in modelling the printing process to address the AM limitations. In metal AM, ML is mainly applied to challenges related to the porosity formation, lack of fusion, surface roughness and other mechanical properties affected by the process parameter that directly affect the final part quality. In more advanced researches, these models can also be used for in-situ monitoring and close-loop control. In ceramic AM, the final quality of the parts is strongly influenced by the post processing activities. As a result, the ML models have to consider both the printing and the post processing stages. Hence, they result particularly useful in predicting dimensional accuracy, mechanical properties, and biological performance.

Therefore, as summarized in Table 5, the ML-AM coupling is more mature in metal AM because the criticalities are observable during printing, while in ceramic systems the most relevant transformations often occur during post-processing.

6.2. Comparative synthesis of ML applications

In metal additive manufacturing processes, machine learning is already applied beyond the conceptual stage, and is increasingly focused on real-world, experimentally validated applications.

Indeed, it is directly integrated into the AM process for optimization, defects detection, and process monitoring, and in some instances even implemented within closed-loop control systems. As discussed in Section 5, metal-based studies frequently employ supervised learning models and ensemble methods to establish direct relationships between process parameters and mechanical outcomes. These models are particularly effective for metals due to the relatively stable and repeatable nature of

Table 5
Comparison between machine learning applications in metal and ceramic additive manufacturing.

Aspect	Metal AM	Ceramic AM
Main stage affecting quality	Printing process	Printing and post-processing
Main criticalities	Porosity, lack of fusion, surface roughness	Shrinkage, densification, cracking, dimensional changes
Typical ML applications	Defect prediction, process modelling, in-situ monitoring, closed-loop control	Prediction of dimensional accuracy, mechanical properties, and biological performance
ML focus	Process modelling, defect prediction, monitoring, control	Prediction of dimensional, mechanical, and biological outcomes
Maturity of ML-AM coupling	More mature, defects are often detectable during printing	Less mature, key transformations occur after printing

the processes, which allows a consistent mapping between inputs and outputs. This indicates a higher level of technological maturity, since ML is also used to support manufacturing decisions and quality control.

Studies on ML applied to the AM of metal implants usually rely on physically manufactured parts, enabling patient-specific customization and allowing tests and mechanical validation on printed implants. These advanced implementations indicate a high level of technological maturity and readiness. Moreover, deep learning approaches, such as convolutional neural networks used for in-situ monitoring, benefit from large datasets of process signals and images, enabling real-time defect detection and quality control.

On the other hand, application of machine learning on ceramic implants fabricated by AM remains at an early stage of the workflows. In literature, most studies focus on structural design, screening and analyses not directly related to the additive manufacturing processes. Researchers tend to concentrate on geometries and material properties rather than process control and optimization. In addition, most of the applications of ML to the additive manufacturing of ceramic implants are still based on simulations and general structure components, lacking definitive prostheses and a full integration of ML with a common workflow. In contrast with metals, the machine learning strategies applied to ceramics are mainly limited to surrogate modelling, inverse design, and property prediction, as highlighted in Section 5. These approaches often rely on regression models or simplified neural networks, which are suitable for design exploration but do not yet enable full process integration or real-time control. Therefore, the lower maturity of ML in ceramic systems should be interpreted as a delay in adoption and because of the different role that ML currently plays in the ceramic manufacturing.

A higher ML maturity in metal usage can be also explained by the mechanic characteristics of the process. Metal additive manufacturing processes are repeatable and stable, with established mechanical testing protocol and direct relationships in the metallic systems. Therefore, the datasets obtained from metal AM are large and well-structured, enhancing a robust application of ML models. This data availability enables the use of more complex models, such as deep neural networks and hybrid frameworks, which require large training datasets to generalize effectively. In ceramics, the additive manufacturing processes are characterized by high variability and sensitivity to defects, especially in the debinding and sintering activities. As a result, the relationship between printing parameters and final implant performance is more indirect and multi-stage. The dataset available for ML models are smaller, often simulation-based, limiting generalization and reproducibility. In addition, ceramic studies usually rely on polymeric based filaments, influencing both the printing and the post-process stages.

The difference in maturity is also reflected in the performance evaluation. When talking about metal implants fabricated by AM, machine learning models are assessed using prediction errors, defect detection rates, geometry accuracy, etc. These metrics are directly connected to implant quality and manufacturing reliability.

With ceramic, researchers tend to measure design-level or material-level indicators. Even if these metrics are relevant, they are not directly related to the printing process or to the reliability of the ML models. This difference reflects the underlying maturity of the ML strategies: in metals, evaluation is closely linked to manufacturing performance, while in ceramics it is often restricted to design level or material level indicators.

Although many studies reported the use of ML in additive manufacturing of implants as a future direction, up to now only metal-based applications have reached a full implementation and experimental validation.

The comparison between metal and ceramic systems suggests that mature ML strategies developed for metal AM cannot be directly transferred to ceramic AM without adaptation. Metal additive manufacturing demonstrates higher reproducibility and are already further ahead in real clinical applications, supported by standardized processes and validated protocols. In contrast, studies involving ceramics are less mature and are not yet generalizable, despite their innovative character.

In conclusion, this synthesis shows that ML in metal implant AM has reached a higher level of maturity because it is supported by direct process–structure–property relationships, richer datasets, and stronger integration with manufacturing and validation workflows. On the other hand, ceramic implant AM remains less mature because implant properties depend on multi-stage transformations that are difficult to observe and model directly. From a methodological perspective, bridging this gap will require adapting the ML strategies successfully used in metals, such as process-integrated supervised learning and data-driven monitoring, to the specific constraints of ceramic manufacturing. This adaptation may rely on hybrid approaches combining experimental and simulation data and physics-based models.

To further clarify the differences between machine learning strategies applied to metal and ceramic additive manufacturing, two tables are provided. Table 6 summarizes the main differences between ML applications in metal and ceramic additive manufactured implants while Table 7 reports the main approaches, their effectiveness in metal systems, and their current limitations and potential adaptations for ceramics.

7. Open challenges and future perspectives

While machine learning has already begun to be part of metal implants fabricated by additive manufacturing, its application to ceramic implants is still constrained by process complexity and limited

Table 6
Comparison of machine learning application in metal and ceramic additive manufacturing of implants. Representative references from the reviewed studies are reported as examples.

Topic	Metal	Ceramic
ML maturity	Real applications [85]	Proof-of-concept [99]
ML-process integration	High [92]	Limited [97]
Datasets	Experimental [86]	Simulated [96]
In-situ monitoring	Yes [80]	Almost absent [98]
Real validation	Yes	Almost absent
Reproducibility	Medium-high	Low

Table 7
Comparison of machine learning strategies in metal and ceramic additive manufacturing of implants. Representative references from the reviewed studies are reported as examples.

ML strategy	Application in metals	Why effective in metals	Limitations in ceramics	Potential adaptation for ceramics
Supervised models [82]	Property and process prediction	Large and consistent datasets	Limited and variable data	Combine experiments and simulations
Deep learning [78]	Monitoring and defect detection	Availability of image/process data	Lack of real-time data	Data augmentation and hybrid models
Surrogate models [95]	Design and performance prediction	Stable input–output relationships	Mainly design-level use	Add experimental validation
Optimization[90]	Design exploration and tuning	Sufficient data for optimization	Data and cost constraints	Use simplified or adaptive methods
Unsupervised learning [87]	Post-process analysis, pattern detection	Availability of large experimental datasets	Limited and non-uniform data	Use synthetic data and feature extraction
Regression models [91]	Fast process estimation	Simpler and stable relationships	Limited for complex behaviour	Combine with nonlinear models

integration.

Looking ahead, there could be a strong opportunity for research in AM of ceramic implants, in which machine learning can play a fundamental role in improving and optimizing the processes, reducing variability, and enhancing reproducibility and reliability.

One of the main challenges lies in the development of high-quality datasets suitable for training the machine learning models. In addition, there is a lack of a fully integrated ML workflow for ceramic additive manufacturing, involving robust process control, defect detection, and optimization.

8. Conclusions

This review paper presents a critical analysis of cases in which machine learning has been applied to the additive manufacturing of implants. In particular, the review includes implants made of metals and ceramics.

The analysis shows a clear gap between metal and ceramic applications. Metal additive manufacturing gains advantage from a repeatable and stable technology, enabling direct integration of machine learning algorithms into printing processes. Several comprehensive cases, covering the entire workflow from design to final real implementation, are included in this work. Ceramic additive manufacturing, on the other hand, is still at a comparative earlier stage. The reported studies show that researchers efforts are still primary focused on design and material screening. Consequently, machine learning approaches are not yet well-integrated into manufacturing workflow nor broadly generalizable.

Overall, machine learning-driven metal implant fabrication through additive manufacturing has reached a mature and clinically relevant stage, while ceramic applications remain comparatively unexplored and represent promising future research directions. The direct transfer of machine learning strategies from metal to ceramic additive manufacturing is not straightforward. While metal-based ML workflows provide useful methodological references, ceramic implant manufacturing requires adapted approaches.

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CRediT authorship contribution statement

Laura Antonini: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Claudio Giardini:** Writing – review & editing, Validation, Resources, Project administration, Conceptualization. **Mariangela Quarto:** Writing – review & editing, Supervision, Formal analysis, Methodology, Visualization. **Carolina Herranz-Diez:** Writing – review & editing, Supervision, Methodology, Formal analysis, Visualization. **Irene Buj-Corral:** Writing – review & editing, Validation, Resources, Project administration, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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Glossary

AI: Artificial Intelligence
AM: Additive Manufacturing
ANN: Artificial Neural Network
ANFIS: Adaptive Neuro-Fuzzy Inference System
BCP: Biphasic Calcium Phosphate
BJ: Binder Jetting
CAD: Computer-Aided Design
CNN: Convolutional Neural Network
DANN: Derivative-Aware Neural Network
DED: Directed Energy Deposition
DIW: Direct Ink Writing
DL: Deep Learning
DLP: Digital Light Processing
DNN: Deep Neural Network
DoE: Design of Experiments
EBM: Electron Beam Melting
EB-PBF: Electron Beam Powder Bed Fusion
FCNN: Fully Connected Neural Network
FDM: Fused Deposition Modelling
FEM: Finite Element Method
GMM: Gaussian Mixture Model
GPR: Gaussian Process Regression
LPBF: Laser Powder Bed Fusion
LCM: Lithography-based Ceramic Manufacturing
MEX: Material Extrusion
MJ: Material Jetting
ML: Machine Learning
PDMS: Polydimethylsiloxane
PLA: PolyLactic Acid
PLGA: Poly (lactic-co-glycolic acid)
PBF: Powder Bed Fusion
RNN: Recurrent Neural Network
SLM: Selective Laser Melting
SNN: Shallow Neural Network
SVM: Support Vector Machine
TPMS: Triply Periodic Minimal Surfaces
VPP: Vat Photopolymerization